Reliability Engineering and System Safety 201 (2020) 106964

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Data driven approach to risk management and decision support for dynamic positioning systems

Tarannom Parhizkar[a,*], Sandra Hogenboom[a], Jan Erik Vinnem[a], Ingrid Bouwer Utne[a]

[a] Department of Marine Technology, Norwegian University of Science and Technology (NTNU), Trondheim, Norway

ARTICLE INFO

Keywords:
Risk management model
Risked-informed decision-making
Data driven model
SPAR-H method
Dynamic positioning (DP) system
Decision support tool

ABSTRACT

Offshore oil and gas operations are inherently associated with risk and may have catastrophic consequences to life, property, and environment. Risk management is thus performed during the design, planning, and operation phases to control risk. Operational risk models are only periodically updated and do not always reflect the available real-time data. This is also the case for dynamic positioning (DP) operation. Monitoring the risk levels of the system during the operational phase could reduce the accident risk by providing additional decision support information for operators.

In this paper, a framework for the risk management of DP operation is proposed to assist operators in decision-making. The risk management output will provide operators a real time risk status and pre-warnings of possible deviations in the system. This framework is developed to support the decision-making process of the operators with providing failure probability of alternative decision scenarios, and it can be applied to any other engineering system and operation.

In order to validate the effectiveness of the framework, DP drilling operations are considered as a case study. The results demonstrate the value and effectiveness of the framework, which reduces the risk level of operations by contributing to the risk-informed decision-making of operators.

1. Introduction

Over the past few decades, online risk-informed decision-making has performed an increasingly important function in aerospace, nuclear, and marine technologies [1,2]. The frequency of dynamic positioning (DP) system failure is an ever-increasing problem, as reported in [3]. It is therefore necessary to further identify fundamental techniques for improving the DP system to reduce its failure frequency.

The safety improvements resulting from online risk management applications lead to advanced improvements in system operation [4,5]. For this reason, online risk monitoring and risk management are necessary to reflect system changes and enhance the understanding of the current safety state of a system.

The online risk management framework updates the failure probability of the system as necessary to account for the changes in system design and operation, thus improving system comprehension [6]. In contrast to conventional risk management methods, online risk management is presented as a dynamic development process. Generally, online risk management is employed to reflect the real-time risk of the system, thus indicating the actual status of (sub) systems and operational/environmental conditions.

Moreover, during critical situations, the online decision support and alarm system may prevent critical unwanted events or provide earlier situation awareness and increased response time to allow for early manual intervention [7]. The online risk level of the system can be used as an input to a decision support tool in order to aid operators in making better decisions more expeditiously and efficiently. As shown in Fig. 1, the action result returns to the risk management model, and the updated risk value is calculated in real time; this is a continuous iterative process.

Risk-informed decision-making has been applied for many years in different fields, and the role of risk insights in safety-related decision-

Abbreviations: BN, Bayesian network; DP, dynamic positioning; DPO, dynamic positioning operator; ESD, event sequence diagrams; FPSO, floating production storage and offloading; HAZOP, hazard and operability analysis; HEP, human error probability; HFEs, human failure events; HMI, human–machine interface; HRA, human reliability analysis; IEs, initial events; IMCA, International Marine Contractors Association; LOP, loss of position; MLD, master logic diagram; MODU, mobile offshore drilling unit; MRP, marine riser package; NCS, Norwegian continental shelf; OIM, offshore installation manager; PRA, probabilistic risk assessment; PSFs, performance-shaping factors; SPAR-H, standardized plant analysis risk-human reliability analysis; WSOG, well specific operating guideline

* Corresponding author at: Department of Marine Technology, NTNU, 7491 Trondheim, Norway.
E-mail address: tarannom.parhizkar@ntnu.no (T. Parhizkar).

https://doi.org/10.1016/j.ress.2020.106964
Received 6 June 2019; Received in revised form 28 January 2020; Accepted 31 March 2020

Fig. 1. Risk-informed decision-making process.

making has received considerable attention. For instance, in [8], an overall methodology for risk-informed decision-making is proposed. In [9], the necessity of structural repair of aging naval ships is investigated based on risk-informed decision-making. In [10], a value-risk graph that visualizes the risk level of alternative decisions in a manufacturing process is proposed.

According to a literature review, however, research works related to risk-informed decision-making in dynamic positioning systems are limited [11,12]. In [7], the importance of decision support in reducing the shuttle tanker collision risk in floating production storage and offloading is investigated. In their study, the hazard, barriers, and risk reduction potentials are assessed, and the necessity of considering advanced estimation and data assimilation in risk management is discussed.

In this study, a novel framework that facilitates decision-making in DP systems is proposed. The main part of the risk-informed decision-making framework is the risk management model. The risk analysis of the DP system has been studied in detail at different complexity levels. In [13], a conceptual model for risk analysis is proposed. In most research works, the power structure of DP systems is investigated in detail [14,15]. Studies related to the risk and reliability analyses of overall DP systems are limited. In [16], a general fault tree for DP classes 1, 2, and 3 is presented. This study indicates that fault trees can be employed for reliability-based design and maintenance scheduling of multi-megawatt capacity DP systems. The human and organizational factors, some of which are important in incident occurrence, however, are ignored [17]. In this study, these factors are considered in the risk management model. As a result, the decision-making process, as well as the human and organizational factors, is facilitated.

The proposed risk management model quantifies the failure probabilities of different operating scenarios of DP systems and can be used as a basis for developing a decision support tool. One of the main parts in system failure quantification includes component failure frequencies. The sources and research on DP system failure mode quantification are also limited. In this study, failure modes are identified, and the rates of their occurrence are quantified based on the International Marine Contractors Association (IMCA) annual incident reports on DP systems (2004–2015). The data gathered from these reports are filtered (missing and inaccurate data are removed), and the failure frequencies of a generic DP drilling system are presented. Although incomplete, these data provide a comprehensive insight into the failure modes of DP systems. As a result, apart from the failure mode frequencies, the detailed fault trees and risk management model are proposed for DP systems. It should be noted that this dataset is used as a basis for the risk level calculation, and the failure frequencies are updated based on the information gathered over time, as presented in Fig. 1.

The online risk management model should satisfy two basic requirements to be applicable in a decision support tool [18]. First, risk level updating should reflect the information on real system configuration; second, a rapid solution to support the real-time application of risk management and decision-making is necessary. The feasibility of online risk management and decision support tool therefore considerably depends on the conversion and calculation times of the solution methodology. It is thus important to develop a highly efficient calculation engine to enable a rapid solution of the online risk management model.

Probabilistic risk assessment (PRA) is a systematic and comprehensive methodology for evaluating risks associated with a complex system while considering the uncertainties of operational and environmental conditions [19]. In the present study, an efficient solution approach based on the PRA method is proposed. Any significant changes in the system risk level can therefore be perceived by the operator, providing a basis for risk-informed decision-making. The full system description and boundaries utilized in this study are provided in Section 3.1. The main contributions of this study are summarized as follows.

- A comprehensive risk management framework for DP operations is developed.
- Human and organizational factors are considered in the risk management model.
- Failure frequencies are calculated according to IMCA reports from 2004 to 2015.

The paper is organized as follows. A brief overview of the developed framework is introduced in Section 2. The details of the framework are presented in Section 3. In Section 4, a DP drilling unit is presented as a case study and results are presented. In Section 5, the results are analyzed, and the usefulness and drawbacks of the proposed framework are discussed. Finally, conclusions and contributions are presented in Section 6.

2. General concept of risk-informed decision making

A conceptual framework of risk-informed decision-making is presented in Fig. 2.

As presented in Fig. 2, the first step is data collection. Some data are non-observable; hence, these data cannot be considered in the modeling. These data are the main source of model uncertainty, and this limitation is further presented in the Discussion section (Section 5.4-Model uncertainties). Operators' beliefs and desires in controlling the system are examples of non-observable data.

Observable data can be considered in the modeling process and are categorized as online or offline data. Offline data generally include design parameters and system characteristics, because they could be used as model input only at a specific instance. For example, the size of machineries, system dimensions, and material characteristics of components could be considered as offline data. Online data, however, serve as continuous model input. Operating and environmental conditions are examples of online data, which are updated through time. Observable data, including offline and online data, are collected and monitored for further analysis in the first step of the framework.

In the next step, the failure probability of the system is calculated. The failure probability and risk level are quantified by analyzing the system fault tree, event tree, and Bayesian network models. The methodology of risk management is discussed in further detail in succeeding sections. The last step includes decision-making; in this step, the results of the risk management model are analyzed and presented to support system operators in decision-making.

3. Risk management model

An overview of the proposed risk management methodology is presented in this section. Fig. 3 illustrates the flow diagram of submodels of the proposed methodology. In the first step, the boundary of the system should be defined. Based on the system boundary, the preferred end states can be determined. Thereafter, initial events that can lead to the realization of the target end state are determined. In the next

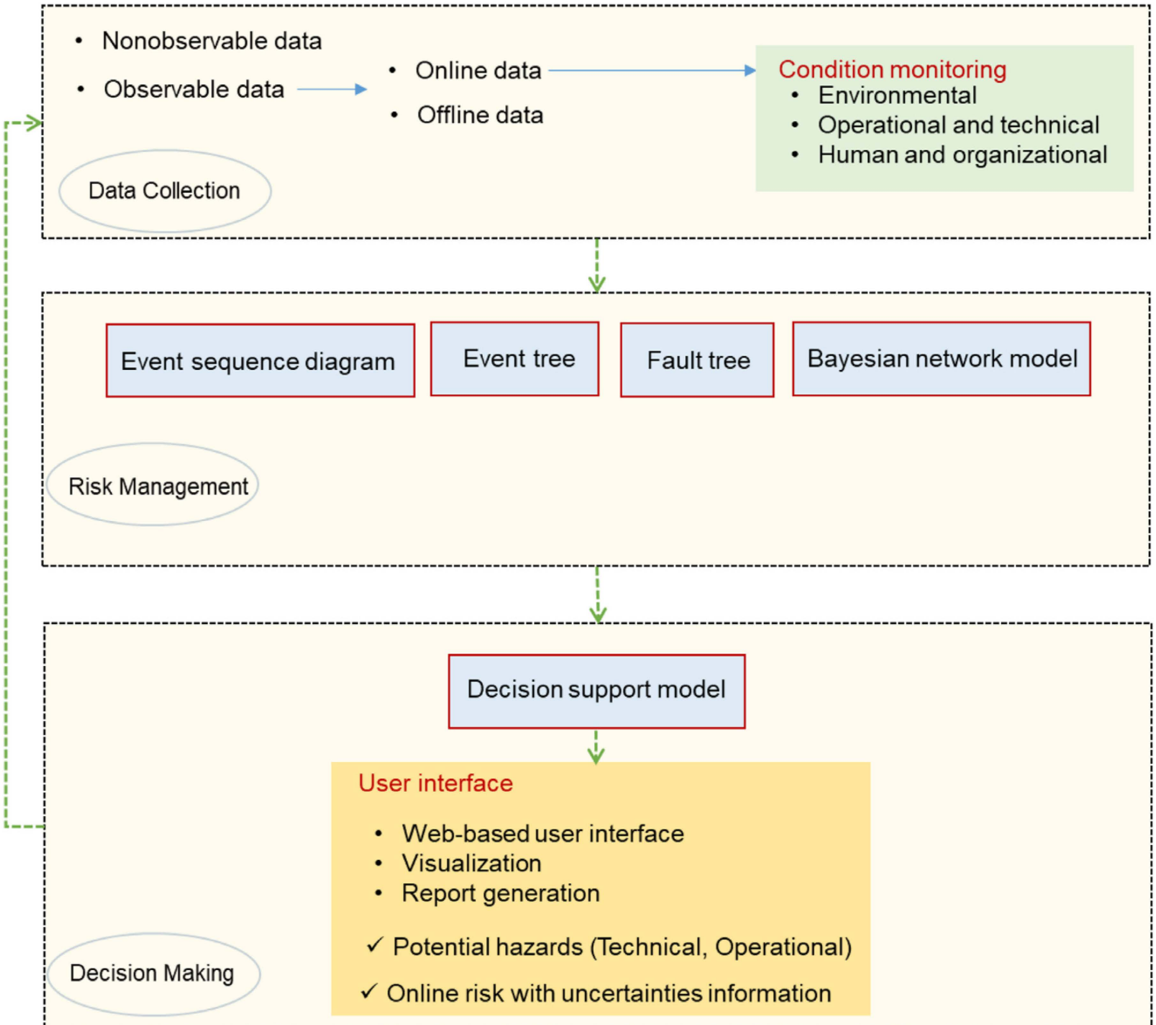

Fig. 2. Conceptual framework of risk-informed decision-making process.

step, event sequence diagrams (ESD), which can aid in deriving event trees, are constructed. Finally, fault trees, Bayesian networks, and decision support models are developed.

In the following sub-sections, the steps of risk management model are presented; and these steps are applied to the dynamic positioning system as a case study. A dynamic positioning (DP) system is a computer-controlled system that can automatically maintain a vessel's position and heading or a predefined track by controlling its own propellers and thrusters. Fig. 4 shows the basic components of a DP system.

It can be observed that the power generation system, switchboard, and thrusters are connected to the DP control system, which gathers data from multiple sensors, including the reference system for position (PRS), gyro compass for heading, motion reference units (MRU), and environmental (wind) sensors. The dynamic positioning operator (DPO) obtains information from the DP control system using the DP console, which is a human–machine interface (HMI) that provides useful information pertaining to the status of components. The DPO could also access other information by means of communication systems, system alarms, and alarm system traffic light.

3.1. Boundary of the study

In the first step, the boundaries of the analysis should be defined, and all components and influencing factors of the system are determined. Based on the desired output, some components/factors are ignored. In the analyzed DP system, the components considered are the propulsion (thruster) system, power system, computer system, and reference system. Moreover, the factors examined include the

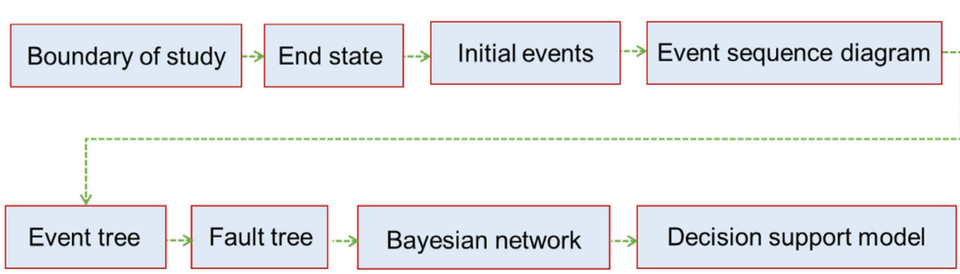

Fig. 3. Sub-models of risk management model.

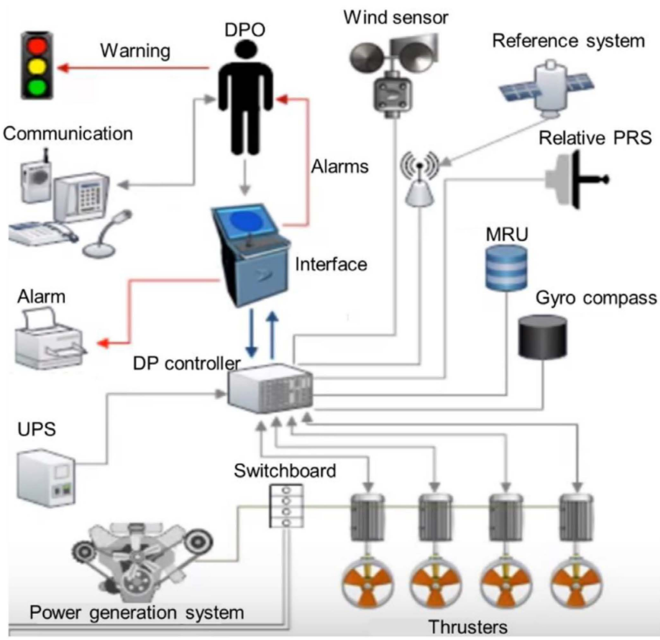

Fig. 4. Dynamic positioning system [20].

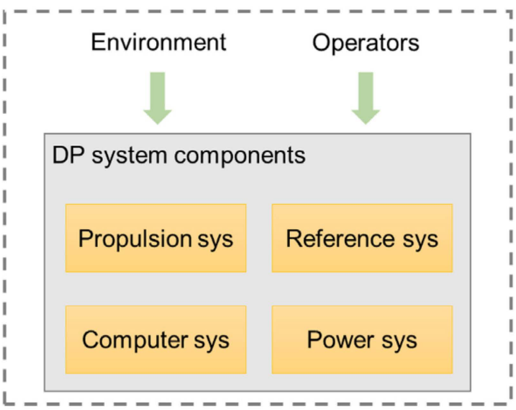

Fig. 5. System boundaries.

environmental and operational conditions (Fig. 5). Human and organizational elements are regarded as influencing factors of the system.

3.2. End states

The end state is a specific situation to be investigated in the final phase of system operation. In this study, the main end state is the loss of position. The end state determines the initial events and critical functions that should be included.

3.3. Initial events

In the third step, the initial events (IEs), which can be defined based on different methods (e.g., hazard and operability analysis (HAZOP) or master logic diagram (MLD)), should be identified. Thereafter, the IEs should be quantified. There are three types of IEs from the quantification perspective. Some IEs are singular events, and their frequency can be calculated based on historical data (e.g., tropical storm in a particular geographical area). Some IEs are more complex and require a fault tree to estimate their frequencies (e.g., inadvertent disconnection of the lower marine riser package). Occasionally, some IEs are conditional (e.g., drift-off because of bad weather). In these cases, the dependencies of IEs should be considered in the frequency quantification. The Bayesian network approach is typically employed to determine the frequency of IEs and data uncertainties. The initial events of the studied DP system are categorized based on the components where events emanate, as summarized in Tables 1–4.

3.4. Event sequence diagram

The event sequence diagram (ESD) shows the interactions of events arranged in a time sequence leading to different end states. This diagram can aid in developing a system of event trees [22]. In this study, the IMCA incident reports from 2004 to 2015 are considered as the most probable ESDs in the DP system [23]. An example of an IMCA incident report is shown Fig. 6.

3.5. Event tree

An event tree is an inductive analytical diagram in which an event is analyzed using Boolean logic to examine the chronological series of subsequent events or consequences. The event tree of the system should be developed based on the ESDs. In this research, the event tree is developed by analyzing all IMCA incident reports from 2004 to 2015. The general event tree for DPs is illustrated in Fig. 7. The first four events present a system loss of position (LOP), and the last event maintains the position status, indicating that the system operates properly (OK).

3.6. Fault tree

In this step, the possible failure modes are identified [24]. The list should be extensive and include all possible failure modes. Those perceived as not probable to occur or with negligible consequence can be eliminated from further consideration at this stage [6]. A fault tree should be developed for the remaining failure modes. In this study, the main failure modes are identified according to the ESDs from IMCA

Table 1
Initial events in propulsion system [21].

Component	Initial events
Thruster unit and drive	Drive short circuits; Main coupling error; DC motor field problem; Overheating; Loose wires
Control system	Pitch or RPM anomalies; Control unit PLC error; Network, communication error; Loose wires/incorrect wiring; Fuse, relay, PCB, and signal amplifier errors; Outstation internal power distribution error; Faulty emergency stop button
Feedback signal	Loose wires/connector; Loose or broken linkages; Faulty potentiometers; Incorrect feedback signal; Feedback failure; Speed sensor failure
Hydraulics (CPP, clutch)	Control valves, proportional, solenoid, and limit switch errors; Low hydraulic oil pressure/pitch pump failure; Hydraulic oil leaks; Gearbox and clutch failure
Propulsion auxiliary systems	Lubrication; cooling pump failure
Cooling, lubrication, air, and ventilation	Thruster brake failure; Cooling, water leak, and thermostat failures; Oil leaks
AC converter	AC converter, Rectifier, Inverter, and DC link failures
Main engine	Scavenge air fan; high exhaust temperature
Human error	Slip; Lapse; Rule-based mistake; Knowledge-based mistake; Routine violation; Optimization violation; Necessary violation

Table 2
Initial events in reference system [21].

Sub-component	Initial event
Interference	High sun activity; Interference from other telecommunication systems; Physical obstruction; Near operations (close proximity to other vessels); Water Aeration; False target; Atmospheric interference
Software	Software error, "OK" after reboot; Software "freeze"; Software "bug"; Wrong settings and IP address; Calibration-insufficient T/C/QA; Update required
Mechanical	Damage caused by corrosion and wear; Taut wire fault; Antenna errors; Damaged/faulty sensor unit or deployment equipment; Heat and fumes from funnel; Position
Communication	Poor differential correction signals from ground station; Ground station computer failure; Signal error caused by satellite maintenance/satellite fault; Loss of satellite feed
Electrical, hardware	Defective card; Loose Connector; Low feed voltage
Service and maintenance	
Human error	Slip; Lapse; Rule-based mistake; Knowledge-based mistake; Routine violation; Optimization violation; Necessary violation

Table 3
Initial events in control system [21].

Sub-component	Initial event
Software	Software upgrade and tuning failures; Software modeling problem; Software "bug" (error, flaw, failure, or fault); Computer "freeze"; Anomaly (controller/ operator station problems); Virus
Hardware	Motherboard failure; Hard drive and circuit board failures; Card failure; Insufficient cooling; Power supply, transmission, and distribution failures; Loose wire; Hardware component failure
UPS	Cooling fan failure; Burnt Card; Voltage control failure; Loose connection; Faulty switch; Charger failure
Human error	Slip; Lapse; Rule-based mistake; knowledge-based mistake; Routine violation; Optimization violation; Necessary violation

Table 4
Initial events in power system [21].

Sub-component	Initial event
PMS	Automatic disconnection of breakers; Faulty controller; Incorrect setup
Control equipment	Governor actuator failure; overspeed; incorrect settings; Incorrect setting of generator actuator; Sensor (e.g., speed) failure; Automatic fuel filter failure; Protection equipment failure (harmonic filter); Loose wire; Air supply failure
Excitation Systems	Voltage and frequency fluctuations; AVR errors; Faulty Diode plate or exciter; Exciter anomaly
Fuel system	Fuel pump failure; Compressed air failure; Blocked filters; Heavy fuel oil separator failure; Water contamination in fuel tanks; Fuel pipe leak; Fuel oil valve failure
Oil system	Pressure drop of isolation valve; Oil pressure sensor failure; Oil leak causing low pressure
Cooling system	Blocked SW strainers; Valve failure; Thermostat failure; Low cooling water pressure; SW pump failure; Leaks
Electrical	Internal short circuit of generator; Fuel supply relay; Earth fault short circuit; Distribution; Cabling; Blown fuses; Transformer, invertor failure
Engine component	Bearing failure; Rocker gear failure; Mechanical failure; Engine overload; Fuel injector failure
Human error	Slip; Lapse; Rule-based mistake; knowledge-based mistake; Routine violation; Optimization violation; Necessary violation

reports. The fault tree of propulsion, reference, power systems, automatic control, and manual control of a DP are presented in Figs. 8–12, respectively. Depending on the specific dynamic positioning operational requirements, the systems are assigned to one of four DP categories (DP classes 0–3). In this study, DP class 2 is explored. DP class 2vessels have redundancy so that no single fault in an active system will cause the system to fail.

The system can be automatically or manually controlled; their fault trees are presented in Figs. 11 and 12, respectively.

3.7. Bayesian network

Human errors can directly and indirectly lead to loss of position. Reason [25] has defined a human error taxonomy based on the three levels of human performance [26]: skill-based, rule-based, and knowledge-based actions. Skill-based actions routinely and automatically occur. Rule-based actions are responses partially controlled and partially performed automatically that are focused on problems. Knowledge-based actions are controlled and applied to novel problems. Human error is defined as the failure of planned actions to realize a goal (without the interference of certain unanticipated events), [27]. These types of errors can be categorized as slips, lapses, rule- and knowledge-based mistakes. Another type of error involves the violations and deviations from safe operating procedures. These safety violations are not malevolent in intent and may be classified as routine, optimizing, and necessary [25].

Human errors can result in the failure of a system function and should be considered in the online risk model [28]. In this study, human reliability analysis (HRA) is employed to estimate the human error probability (HEP) for human failure events (HFEs) in fault trees. In HRA methods, the human error probability is the conditional probability of a failure event given the performance context. The context is analyzed with the standardized plant analysis risk-human reliability analysis (SPAR-H), which is a method that can quantify human risks in a system [7] and assess the probability of human errors for a known context. The analyst determines the underlying context by selecting a set of performance-shaping factors (PSFs), which are discretized into levels or states.

It is not always possible, however, to gather perfect information on the PSF level, and in some cases, the PSFs are not directly measurable or observable [2]. No theory related to the direct causal relationship between various PSFs and human error types exists, indicating that it is

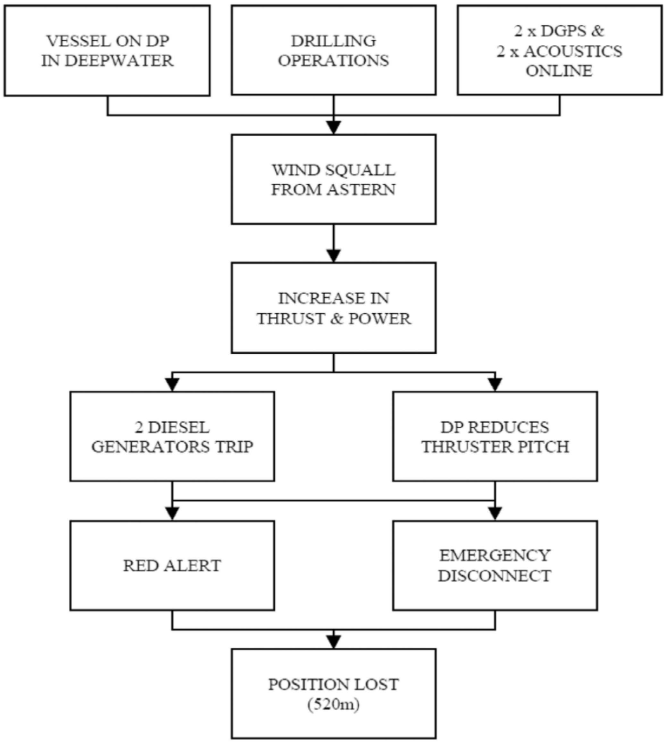

Fig. 6. Sample incident report from IMCA annual DP report [23].

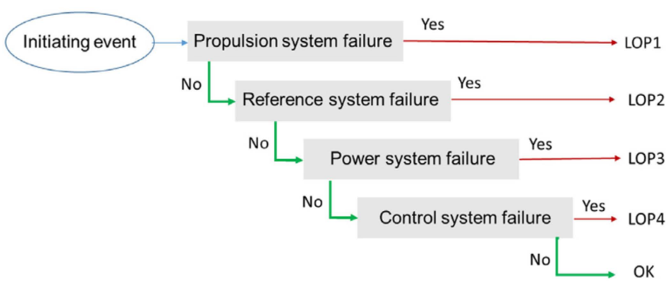

Fig. 7. Event tree of DP systems.

not clear to which degree for example stress affects lapses. All PSFs are therefore linked to all human error types. The relationship between human error types and affected systems is obtained from the data found in the IMCA reports.

In order to reduce the subjectivity associated with the estimated PSF and the HEP from the analyst, prior probabilities in the Bayesian network (BN) are determined, and the network is updated using available observations. Bayesian networks afford several advantages that can enhance the PRA method in human reliability assessment. The Bayesian network of a DP system for the HRA is formulated, as shown in Fig. 13. It should be noted that the first layer (PSFs) is connected to all human error types; for simplicity, however, this is not included in the figure.

These Bayesian networks calculate the human error probabilities in the reference, control, thruster, and power system. Apart from the foregoing, human errors can also occur when the system operates in the manual mode, as presented in Fig. 12. The failure probability of the manual control system can be calculated based on the Bayesian network model in Fig. 14.

3.8. Decision support tool

In the decision support model, alternative decisions should be defined. The risk management model is thereafter employed to assess the risk associated with each alternative decision. The decision with the lowest risk should typically be the preferred decision alternative; however, cost and availability are also important factors that can influence the decision.

Most DP drilling operations in the Norwegian Continental Shelf (NCS) follow a set of well specific operating guidelines (WSOG) that includes procedures/guidelines for operations. It specifies the limits for different DP parameters that indicate the state of the DP system and operation. Typically, there are four states: green, white, yellow, and red. In the green state, all DP operation parameters are within acceptable limits, and the operation can proceed normally. When the DP operation is in a white state, some of the redundancies are lost, or weather conditions have worsened. This state is also called the advisory state because of the necessity for calling an advisory meeting to discuss how operations should proceed. In the yellow state, even more redundancies are lost, and/or weather conditions have further worsened; the vessel remains capable of maintaining position, but the probability is low. In the red state, the mobile offshore drilling unit (MODU) is no longer capable of maintaining position, the operation should be aborted, and under most circumstances, the unit should be moved to the safe zone at the earliest possible time.

The WSOG is extremely prescriptive and stipulates the actions required in case the DP system loses its redundancies, or weather conditions are unfavorable. This is especially true for the green state (all

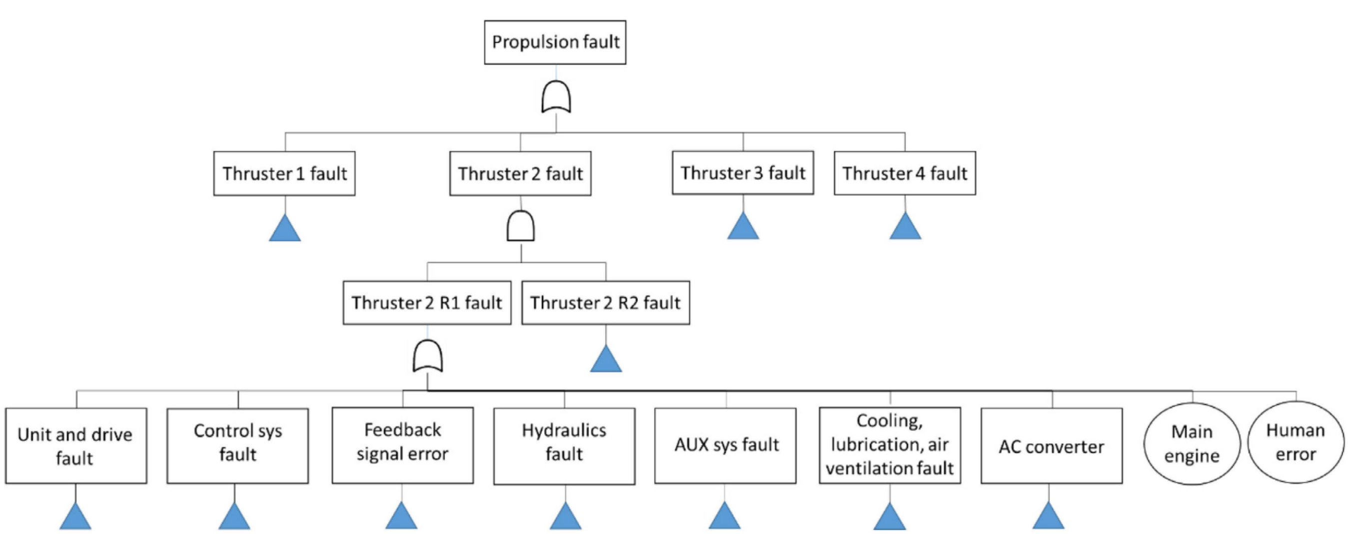

Fig. 8. Propulsion system fault tree of a DP class 2 system.

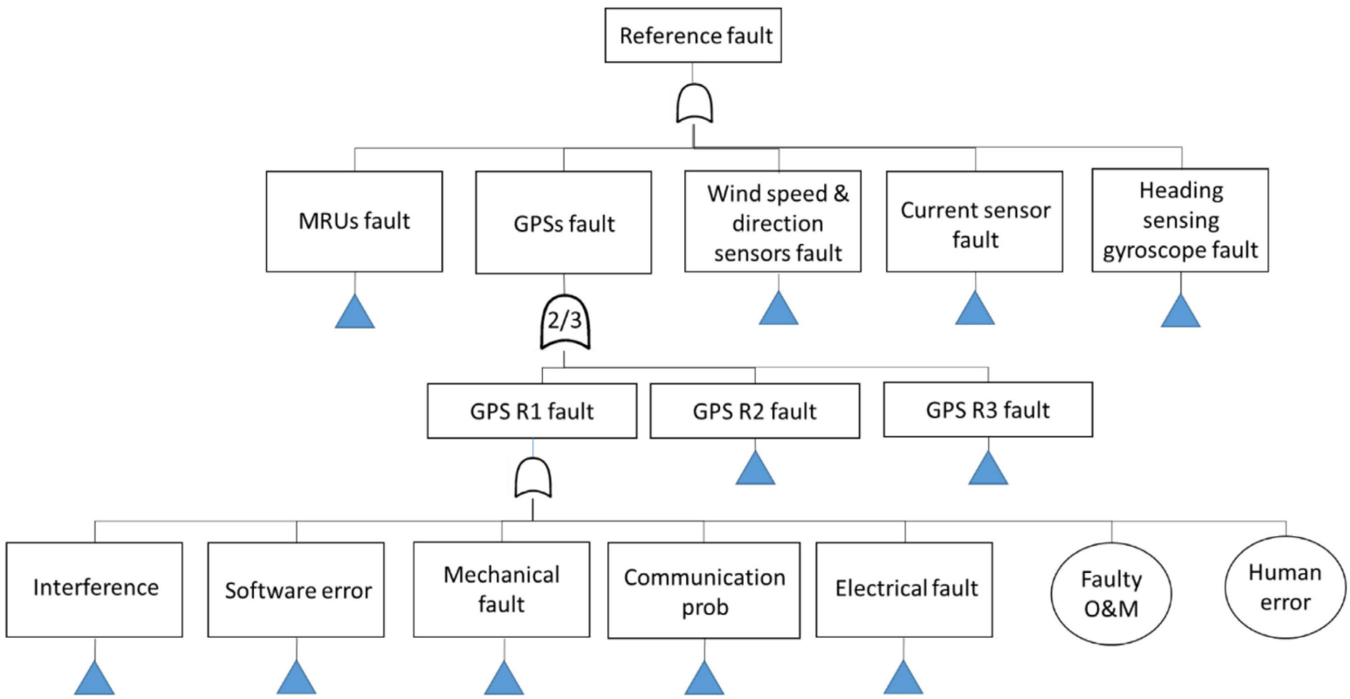

Fig. 9. Reference system fault tree of a DP class 2 system.

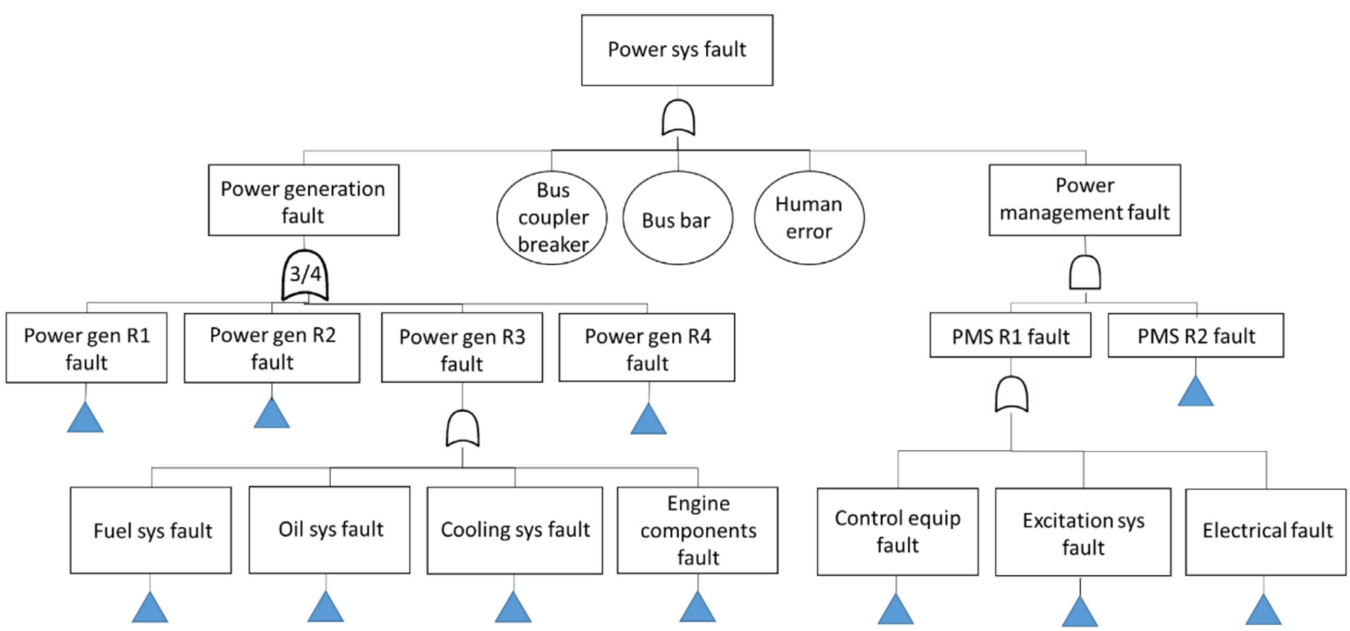

Fig. 10. Power system fault tree of a DP class 2 system.

systems are operational, and all conditions are within operational limits) and red state (redundancy within the DP system is compromised to the extent that the vessel encounters difficulty in or is not capable of maintaining position). During the advisory and yellow states, the time for evaluation remains available because the capability of maintaining position is not directly threatened. Situational factors, however, should be evaluated to determine the risks associated with various decision alternatives, i.e., whether the MODU stays or moves to the safe zone. It is certain that additional decisions have to be made. If the MODU stays, are additional risk reduction measures necessary? If it is moved to the safe zone, what is the best way to do so? The decision support tool presented in this paper aims to provide input in making these decisions.

4. Risk management model applied to a MODU drift-off incident at Skarv field

An incident investigation report of a MODU is used to study the applicability of the developed framework. Mobile offshore drilling units are employed in the exploratory offshore drilling of new oil and gas wells. They rest on columns and pontoons and can be moored with anchors. For deep water drilling operations, however, these units (such as the studied MODU in the presented incident investigation report) rely on the DP system to maintain position. The DP system of MODUs follows the same rules as other types of DP systems, and their risk levels could be calculated using the method presented in Section 3.

In the following sections, the incident is first described according to

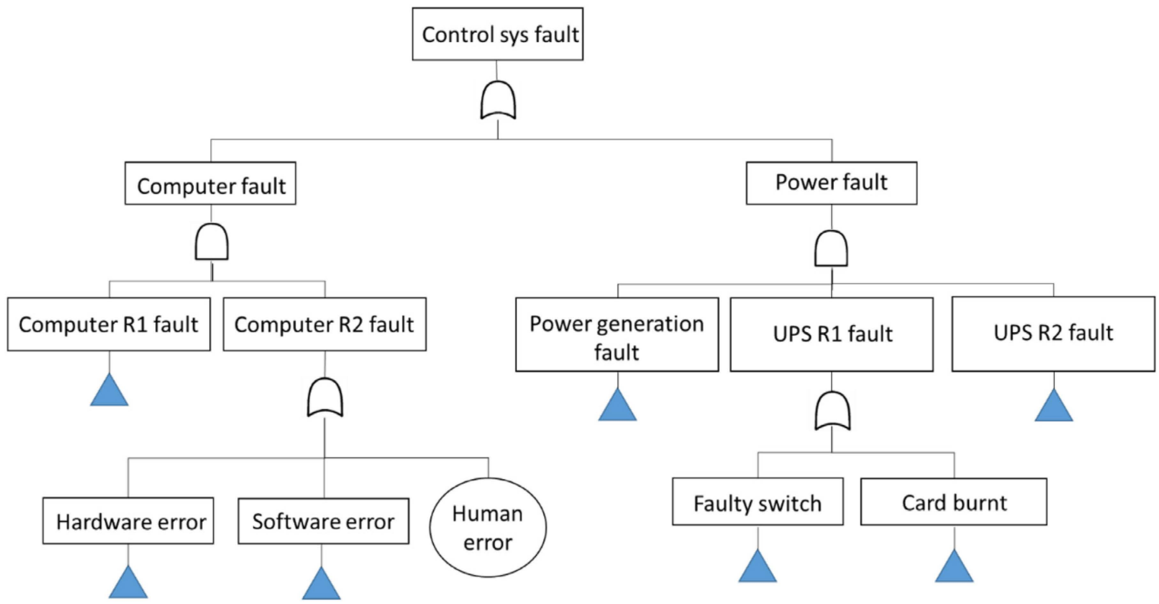

Fig. 11. Automatic control system fault tree of a DP class 2 system.

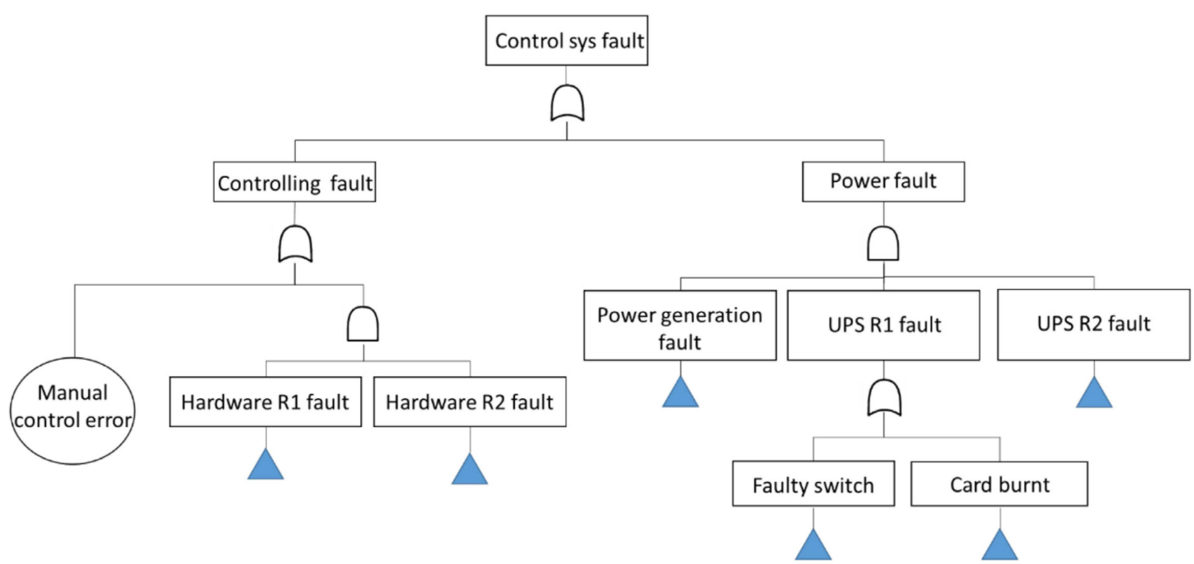

Fig. 12. Manual control system fault tree of a DP class 2 system.

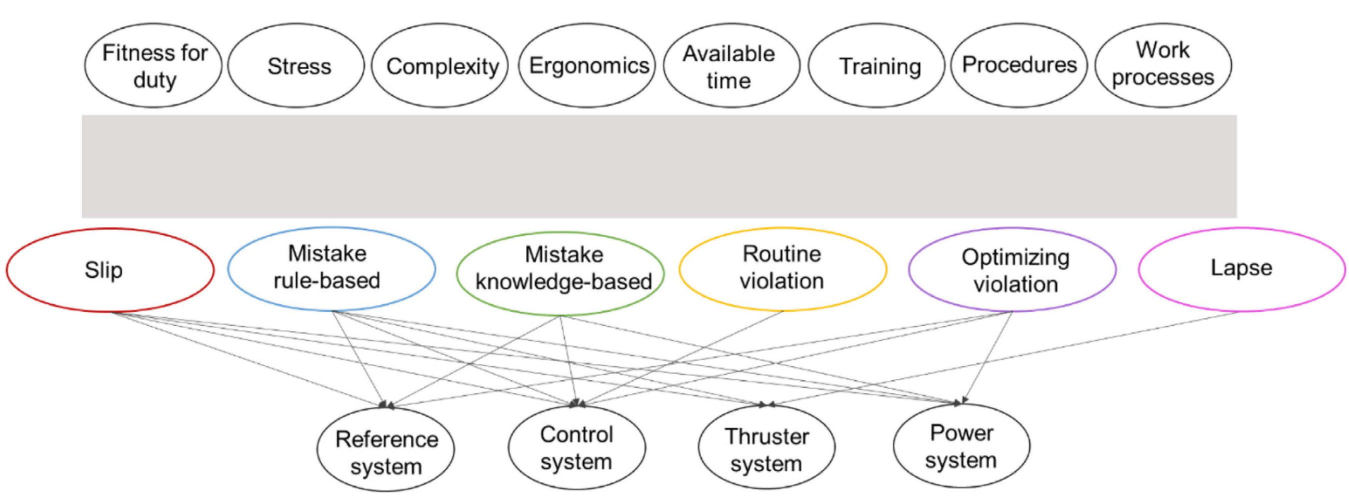

Fig. 13. BN for HRA of DP class 2 system (Section 3.6).

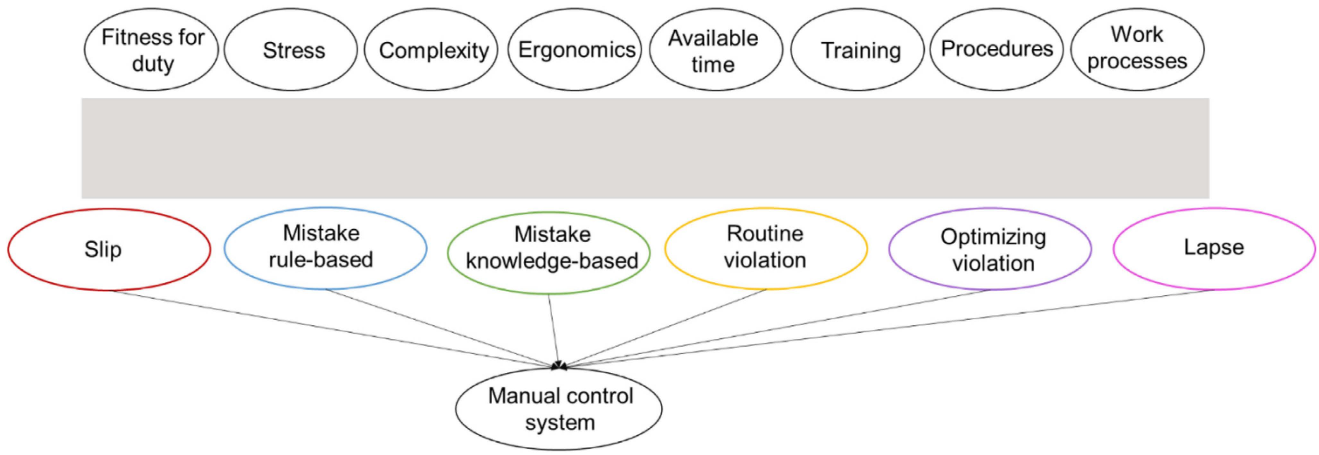

Fig. 14. BN for HRA of DP class 2 manual control system.

the investigation report, and the different scenarios generated to study the effectiveness of the proposed model are elaborated. In Section 4.2, a data flow diagram of the proposed risk management model for the case study is presented. This diagram indicates the required input to the model introduced in Section 4.3. Finally, the results of different scenarios are discussed and compared in Section 4.4.

4.1. Description of incidents and scenarios

In the Deepsea Stavanger platform, on April 2018 at 12:38, it is observed that the MODU has lost position during a riser workover and float tree installation on well A-03 [29]. A detailed course of events is presented in Fig. 15. During this incident, the MODU has exceeded the limits for the advisory, yellow, and red states. The WSOG for the Deepsea Stavanger specifies that in the red state, the offshore installation manager (OIM) has the discretion to decide whether the situation threatens the equipment and what actions to take. In this case, the OIM observed that the speed at which the MODU was moving off position was decreasing and accordingly expected that the vessel will immediately regain position. The OIM therefore decided not to disconnect and move the MODU to the safe zone; instead, the automatic disconnect was inhibited while waiting for the MODU to regain its position with the DP system. The vessel regained position after having a maximum excursion of 12 m. The ESD of the incident is presented in Fig. 15.

In this study, the event is analyzed using the SPAR-H method. Apart from the scenario described in the incident report (Scenario 1), an alternative scenario is also analyzed (Scenario 2). In this alternative scenario, it is assumed that the OIM is not on the bridge and that the dynamic positioning operator (DPO) is responsible for the decision-making and handling of the loss of position. This scenario is included to present a realistic alternative decision-making situation and how this affects the risk status.

In Scenario 1 (Fig. 15), both the OIM and DPO are on the bridge when several high waves push the MODU off position. Moreover, the thrust to keep the MODU in position is insufficient because the ongoing drilling operation is consuming power; consequently, drift-off occurs.

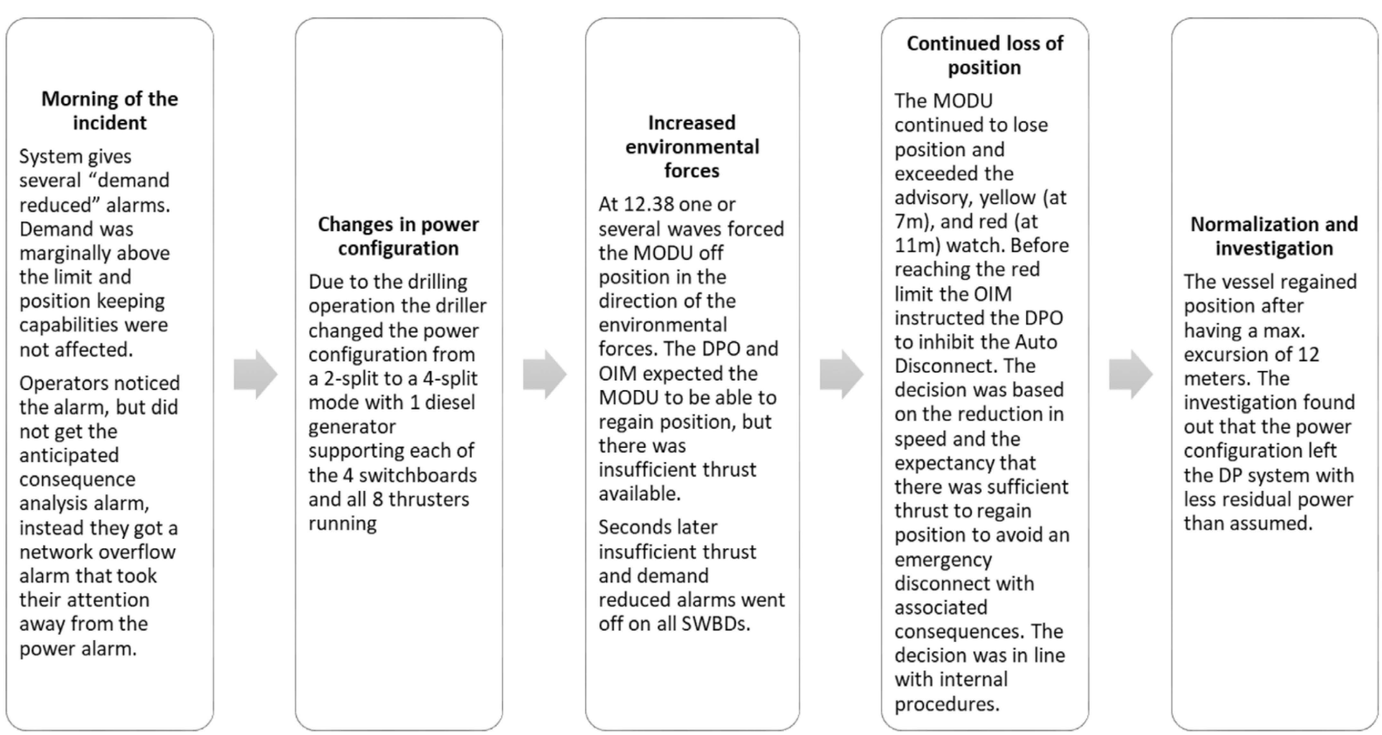

Fig. 15. Event sequence of Deepsea Skarv incident based on investigation report [29].

Between the first wave and the 12-m excursion, the maximum response time is 1 min. Scenario 2 is similar to Scenario 1. The MODU is pushed off position by several high waves. Further, the thrust necessary for the MODU to maintain position is insufficient because the ongoing drilling operation is consuming power; as a result, drift-off occurs. The difference between Scenario 1 and 2 is the manning on the bridge. In Scenario 1, similar to the incident on the Deepsea Stavanger, the OIM and DPO are both on the bridge. In Scenario 2, however, it is assumed that the OIM is unable to reach the bridge on time, leaving the DPO to handle the drift-off alone.

The loss of position probabilities under automatic and manual conditions are calculated for each scenario. The control systems in the ESD for manual and automatic modes differ. In the automatic mode, the DP model controls the system, and the failure probability is calculated using the presented fault tree in Fig. 11. In the manual mode, however, with a human operator involved, the failure probability is calculated using the fault tree in Fig. 12 and the Bayesian network in Fig. 14.

4.2. Data flow diagram of case study

In this section, the data flow of the proposed model and the derivation of results from input parameters are presented. The data flow for the reference system is shown in Fig. 16. The data flows for the thruster, control, and power system are the same. The first layer involves BNs. In this level, human error probabilities are calculated based on PSFs and IMCA incident reports. Its outputs are human errors related to power, propulsion, control, and reference systems. The values and failure frequencies of components obtained from IMCA reports update the basic event probabilities/frequencies in all fault trees. The figure shows the fault tree of the reference system as an example. The model considers all other fault trees, including those of power, propulsion, and control systems. The failure probabilities of these systems are then used as input by the ESD, and the probabilities are calculated according to the initial event.

4.3. Frequency/probabilities of basic events in case study

As presented in Fig. 16, the frequency/probability of basic events should be considered as model input. In this section, these values are evaluated based on available historical data. Specifically, the frequency/probability of basic events are derived using the IMCA annual incident data on DP drilling units from 2004 to 2015. The failure frequencies of components are presented in Section 4.3.1. In addition, the human error probabilities are quantified using BNs, as presented in Figs. 13 and 14. The quantification process is presented in Section 4.3.2.

4.3.1. Component failure frequencies

Operating hours

The operational times of DP vessels from 2004 to 2010 are gathered

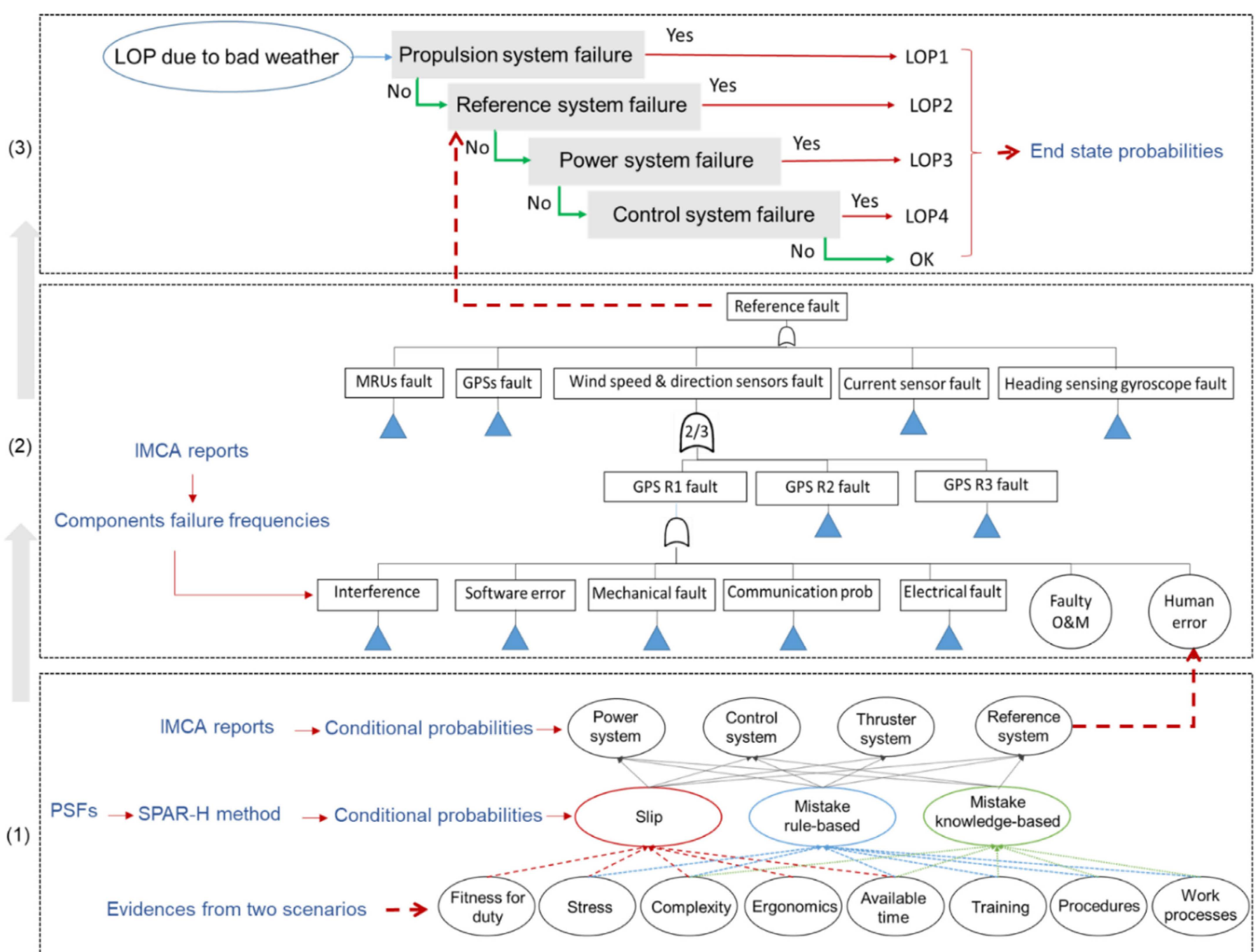

Fig. 16. Data flow of case study.

Table 5
Operational times of drilling DP from 2004 to 2015 worldwide [30].

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Operating hours (year)	49.4	49.7	50.3	50.3	72.1	80.6	89.5	87.5	93.2	98.9	104.7	110.4

Table 6
Failure frequencies of thruster sub-systems in DP drilling unit based on IMCA incident report.

Failure group	Causes	Frequency per hour[1]
Thruster unit and drive	Main coupling error	1.22E−07
	DC motor field problem	1.22E−07
	Unknown	4.88E−07
Control system	Control unit PLC error	2.44E−07
	Fuse, relay, PCB, and signal amplifier errors	2.44E−07
	Outstation internal power distribution errors	2.44E−07
	Unknown	6.09E−07
Feedback signal	Loose or broken linkages	1.22E−07
	Faulty potentiometers	1.22E−07
Hydraulics (CPP, clutch)	Control valve, proportional, solenoid, and switch errors	1.22E−07
	Low hydraulic oil pressure/ pitch pump failure	1.22E−07
Cooling, lubrication, air, and ventilation	Thruster brake failure	1.22E−07
	Oil leaks	1.22E−07

[1] Numbers are rounded off for the purpose of reporting.

from drilling semi-submersibles and drill ships worldwide [30], and the operating hours for the other years are estimated based on the available data trend. The total operational time over a 12-year span is 937 years.

Frequencies

The failure frequency is calculated from Eq. (1), and the number of incidents is gathered from IMCA reports. The operating hours are summarized in Table 5.

$$fr = \frac{Number\ of\ incidents}{Hours\ of\ operation} \tag{1}$$

The failure frequencies of all initial events of components are summarized in Tables 6–9.

4.3.2. Human and organizational error frequencies

The human and organizational errors are quantified based on the BN model. The structure of the BN for the DP drilling unit is presented in Fig. 13. The structure is derived based on information gathered from IMCA reports.

The human failure event for these two scenarios is defined as failure to handle a drift-off. The focus is on the diagnosis and decision-making in incident scenarios. The PSFs of the two scenarios are presented in Table 10.

Table 7
Failure frequency of reference sub-systems in DP drilling unit based on IMCA incident report.

Failure group	Causes	Frequency per hour[1]
Interference	Physical obstruction	1.22E−07
	Atmospheric interference	1.22E−07
Software	Wrong settings, IP address	1.22E−07
	Calibration-insufficient T/C/QA	1.22E−07
	Unknown failures of the software	1.22E−07
Mechanical	Damaged/faulty sensor unit or deployment equipment	4.88E−07
Communication	Loss of satellite feed	3.66E−07
Unknown	Unknown	1.22E−07

[1] Numbers are rounded off for the purpose of reporting.

Table 8
Failure frequency of control sub-systems in DP drilling unit based on IMCA incident report.

Failure group	Causes	Frequency per hour[1]
Software	Software modeling issues	3.66E−07
	Anomaly (controller/operator station problems)	4.88E−07
Hardware	Motherboard failure	1.22E−07
	Hardware components failure	1.22E−07
UPS	Unspecified errors	2.44E−07
	Faulty switch	1.22E−07

[1] Numbers are rounded off for the purpose of reporting.

Table 9
Failure frequencies of power sub-systems in DP drilling unit based on IMCA incident reports.

Failure group	Causes	Frequency per hour[1]
Control equipment	Faulty controller	1.22E−07
	Unknown	1.22E−07
	Governor actuator failure, overspeed, and incorrect settings	3.66E−07
	Generator actuator and incorrect setting	2.44E−07
	Sensor (e.g., speed) failure	1.22E−07
	Protection equipment failure (harmonic filter)	2.44E−07
	Unknown	1.22E−07
Electrical	Generator internal short circuit	2.44E−07
	Fuel supply relay failure	1.22E−07
	Short circuit and earth fault	3.66E−07
	Distribution, cabling, grounding, and blown fuses	1.22E−07
	Transformer and invertor failure	1.22E−07
	Bus bar failure	1.22E−07
Engine component	Engine overload	3.66E−07
Fuel system	Compressed air failure	2.44E−07
	Fuel pipe leak	1.22E−07
Cooling system	Blocked SW strainers	1.22E−07
	Unspecified errors	1.22E−07

[1] Numbers are rounded off for the purpose of reporting.

The parameters in the table are summarized as follows.

(a) Based on the information available from the incident, sufficient time is available to perform the action; hence, the available time is considered nominal.
(b) Based on the available time and with the OIM on bridge, it is assumed that the DPO has sufficient time to act during the incident.
(c) Based on the description of the incident, an automatic or manual emergency disconnect would have been triggered if its functionality is not inhibited. Without the OIM on the bridge, however, only the DPO made the decision to restrain the disconnect, which had potential safety and financial consequences.
(d) In the Skarv incident, the OIM had a good overview of the situation and can control it. The PSF stress is therefore considered nominal.
(e) In the incident description, it is not evident whether the diagnosis is easy or difficult. Accordingly, complexity is evaluated as having a nominal effect on HEP.

Table 10
PSF factors of Deepsea Skarv incident and alternative scenario without OIM on bridge.

PSFs	PSF levels	Evaluation of PSFs of incident with OIM on bridge Scenario 1	Evaluation of PSFs of incident without OIM on bridge Scenario 2
Available time	Nominal	a	b
Stress	High	–	c
	Nominal	d	–
Complexity	Nominal	e	f
Training	High	g	–
	Nominal	–	h
Procedures	Available but poor	–	i
	Nominal	j	–
Ergonomics	Nominal	k	l
Fitness for duty	Insufficient information	–	m
	Nominal	n	–
Work processes	Insufficient information	–	o
	Nominal	p	–

(f) In the incident description, it is not evident whether the diagnosis is easy or difficult. Accordingly, complexity is evaluated as having a nominal effect on HEP.
(g) The OIM is considered to have an extensive experience with DP. Training and experience are therefore evaluated as high.
(h) This scenario is hypothetical; hence, no assumptions are made on the level of experience or training of the DPO.
(i) The limited description of the scenario is presumed to lead to a difference in approach between the DPO and OIM. The procedure indicates that handling such a situation is dependent on the OIM's discretion. If the OIM is not available, however, then it is assumed that the DPO may make the decision to disconnect and move the MODU to a safe zone to stabilize the power distribution.
(j) Procedures are available and are relatively simple and straightforward; however, they are not particularly descriptive. The effect of procedures is therefore considered to be nominal.
(k) No information is available on the state of ergonomics/HMI.
(l) No information is available on the state of the ergonomics/HMI.
(m) This situation is hypothetical; hence, no assumptions are made on the fitness for duty of the DPO.
(n) The OIM is capable of performing tasks, but performance degradation is not described. The PSF is therefore considered nominal.
(o) In the incident description, there is insufficient information on the effect of work processes on the performance of DPO.
(p) In the incident description, decision-making seems to have been performed unilaterally by the OIM. It is therefore considered that work processes are not performance drivers.

Table 11 summarizes the PSFs for a DPO action in the DP drilling unit.

The conditional probabilities are calculated by Eq. (2) [31].

$$CP = \frac{0.01 \times \prod PSFs}{0.01 \times (\prod PSFs - 1) + 1} + \frac{0.001 \times \prod PSFs}{0.001 \times (\prod PSFs - 1) + 1} \tag{2}$$

The first term represents the conditional probabilities of the human error probability (HEP) of a diagnostic task (e.g., decision-making), and the second term shows the HEP of an action task (e.g., pushing a button). The conditional probabilities of slip, rule-based mistake, and knowledge-based mistake nodes are calculated using Eq. (2). It should be noted that for the two factors, i.e., inadequate available time and unfitness for duty, the final conditional probabilities are assigned to be 1, regardless of the other PSF levels.

The conditional probabilities from human error to failures in the reference, control, propulsion, and power systems are calculated based on the information gathered from IMCA reports.

Table 11
PSFs of case study.

PSFs	PSF levels	Multiplier
Available time	Inadequate time	P(failure) = 1
	Nominal	1
Stress	High	2
	Nominal	1
Complexity	Highly complex	5
	Nominal	1
Training	High	0.5
	Nominal	1
Procedures	Available but poor	5
	Nominal	1
Ergonomics	Poor	10
	Nominal	1
Fitness for duty	Unfit	P(failure) = 1
	Nominal	1
Work processes	Poor	2
	Nominal	1

4.4. Results

In this section, the results of the application of risk management framework in the case study are presented. As mentioned earlier, two scenarios are compared.

- Scenario 1: The offshore installation manager (OIM) is on the bridge and has the discretion to decide whether the situation is a threat to equipment and what actions to take.
- Scenario 2: The OIM is not on the bridge, and the DPO is solely responsible for decision-making and handling of loss of position.

The first three rows present the three human error types (slip, rule-based mistake, and knowledge-based mistake) considered in this study. It can be observed that slip and mistake probabilities significantly increase from Scenario 1 to scenario. The OIM is not on the bridge in the second scenario; hence, human error probability increases. This type of error is largest in the rule-based mistake category because of the significance of training and experience on the PSF.

The rows in Table 12 indicate that human errors occur in different components, such as power, reference, thruster, and control systems. It is observed that human errors are lower in Scenario 1 because of the presence of the OIM.

As presented in the ESD (Fig. 7), five end states, including the LOPs caused by propulsion system failure, reference system failure, power system failure, control system failure, and keep safe position (“OK”),

Table 12
Human error probabilities for different components in two scenarios.

	State	Scenario 1	Scenario 2
Slip	Yes	0.0022	0.0222
	No	0.9978	0.9778
Rule-based mistake	Yes	0.0110	0.1011
	No	0.9890	0.8989
Knowledge-based mistake	Yes	0.0110	0.0511
	No	0.9890	0.9489
Human error in power system	Healthy	0.9921	0.9432
	Faulty	0.0079	0.0568
Human error in reference system	Healthy	0.9953	0.9641
	Faulty	0.0047	0.0359
Human error in thruster system	Healthy	0.9981	0.9819
	Faulty	0.0019	0.0181
Manual control error	No error	0.9779	0.8358
	With Error	0.0221	0.1642
Automatic control system	Healthy	0.9916	0.9430
	Faulty	0.0084	0.0570

Table 13
End state probabilities in manual and automatic modes for two scenarios. (LOP: loss of position).

	Scenario 1		Scenario2	
	Automatic	Manual	Automatic	Manual
LOP 1	0.0020	0.0020	0.0181	0.0181
LOP 2	0.0042	0.0042	0.0315	0.0315
LOP 3	0.0056	0.0056	0.0391	0.0391
LOP 4	0.0040	0.0218	0.0271	0.1496
"OK"	0.9843	0.9664	0.8842	0.7616

are defined for the case study. Table 13 summarizes the probabilities of occurrence of end states in the ESD. In the list, two operation modes are considered for each scenario.

- Automatic mode: the DP system automatically maintains the vessel position using the control system and related actuators.
- Manual mode: operators use a joystick to control the position and heading of the DP system.

It is observed that for the first three end states (LOP 1–3), there is no difference between the probability of failures under the manual and automatic operation modes. This lack of difference is attributed to the fact that the power, thruster, and reference systems are independent from the manner the systems are controlled. The fourth end state (LOP 4), however, presents the control system failure, and the probability of this state is considerably affected by the control method (manual or automatic).

The significance of human factor is observed in End 4 where the probability of failure considerably increases between the automatic and manual operation modes for both scenarios. This increased probability in the manual mode is more significant under Scenario 2, due to lower manning where the human factor is more consequential due to higher stress level and lower level of training and procedure. Comparison of the two scenarios indicate the importance of the training factor since the probability of failure in the manual mode under Scenario 1 is even lower than the probability failure in the automatic mode under Scenario 2.

The details summarized in Table 13 could aid operators in making better decisions. In the list, the "OK" probabilities of automatic and manual modes could be compared, and the operator could select the mode of operation based on these values. In these two scenarios, the probability of "OK" in the automatic mode is higher; it is therefore more advantageous to attempt to use the automatic mode in maintaining the vessel position.

The unavailability of various systems is listed in Table 14. The values indicate the proportion of time that DP components are not in a functioning condition, as calculated by Eq. (3):

$$U = \frac{Down\ time}{Total\ time} = \frac{MTTR}{MTTR + MTTF} \tag{3}$$

where MTTR is the mean time of repair; MTTF is the mean time of failure. The unavailability values for the manual and automatic modes for the thruster, reference, and power systems are the same, but different for the control system. In Scenario 2, all values are significantly higher because of the human error factor and the effect of training and procedure in Scenario 1. The largest increase in unavailability between Scenario 1 and Scenario 2, however, occurs in the manual control system where the human factor is more critical.

Table 14
Unavailability of DP components in two scenarios.

	Scenario 1	Scenario 2
Thruster system	0.0020	0.0181
Reference system	0.0048	0.0359
Power system	0.0079	0.0568
Automatic control system	0.0084	0.0570
Manual control system	0.0221	0.1642

The results summarized in Tables 13 and 14 could serve as input to the decision support tool. The unavailability of different DP components is part of the risk levels associated with remaining in location. The results also indicate means of leaving the location (if necessary) by using the unavailability values of the manual and automatic control systems as input.

5. Discussion

5.1. Applicability of proposed risk management model

In order to evaluate the effectiveness of the model, a case study with two operating scenarios is employed. The comparison between the results derived from the two scenarios indicates the sensitivity of the model to the PSFs of an operator. According to the results, when the stress level is high and the procedures are inadequate, the system failure probability is high (as expected). This demonstrates the usefulness of the model. Moreover, two operational modes, manual and automatic, in each scenario are compared. These comparisons illustrate how the model effectively reacts to the change in system defaults. For example, when the operating mode is shifted from automatic to manual, the human error level would be higher. This is mainly because human interaction in the manual mode would be higher, thereby leading to a high level of human error, as clearly indicated by the results.

5.2. Implications of presented results

According to the analysis data from IMCA reports, the fault trees of the DP system are highly dependent on vessel type and operational mode.

The presented model is applicable for a general type of DP class 2 in a drilling vessel (Section 3.6). As the component redundancy options for DP class 3 are improved is far wide and multiple alternative combinations can be designed for DP class 3, we focused on DP class 2 for more generalizing. In addition, DP class 3 analysis will provide higher reliability level; however, the relative risk level between the scenarios will remain the same. So, the provided results are applicable for DP class 3 as well.

Practically, the values of initial event frequencies, as well as conditional probabilities of human errors should be continuously updated according to the incident data of a vessel that utilizes the model. As presented in Fig. 16, the input parameters of the model at each step are updated. Each reported failure updates the human error probability or failure frequency according to the initial failure event. The recorded failures resulting from human error updates the conditional probabilities of human error in step 1 of the diagram because this step indicates the system failure probabilities caused by human errors. Moreover, the failures resulting from system technical problems update the failure frequencies in step 2 of the diagram because this step shows the failure rate of components.

It is further observed that in all cases, the automatic mode has a lower failure probability. This is mainly because human interaction in the manual mode is more considerable compared with that in the automatic mode, and human error significantly affects the failure probability of the system. As a result, the model suggests automatic mode to the decision support tool as it has a lower failure probability in most cases. In reality, however, other factors, such as cost and time, may have a considerable impact on the decision-making process. A decision support tool that simultaneously considers all factors should therefore be developed.

5.3. Quality of input data

The study and parts of the analyses considerably rely on the IMCA reports and available information. It is difficult, however, to verify the quality of incident information included in the IMCA reports because they are not in their original form. It is also possible that the original incident investigation is not sufficiently thorough to provide insights on the causal factors or is not performed by people with the appropriate competencies. The incident descriptions in the IMCA reports are typically brief and insufficient in detail, thereby requiring interpretation and subjectivity. This is therefore among the limitations of data quality. Another possibility is that underreporting has to be assumed. The IMCA reports are based on incidents that have been voluntarily shared by various vessel owners. It is possible, however, that a complete overview has not been provided. The extent of to which incident details are missing from the IMCA reports can only be surmised. It is generally important to note that data quality can be compromised at any stage of the data process because of the following reasons.

1 Underreporting
2 Missing or incomplete data or errors in data collection and entry
3 Differences in the application and comprehension of variable definitions

In this study, it is assumed that there is no bias in the available data obtained from IMCA. Datasets, however, can be assessed for levels of underreporting and data quality through comparison with other databases. A common comparison to make is between IMCA reports and available investigation reports. Another means is the utilization of the failure rate of components. Although these evaluations are extremely useful, it is impossible to determine the real frequencies and failure rates because the exact intersection of the two databases cannot be obtained [32].

The drift off at the Skarv field, is used to exemplify the model. The incident report is in its original form that is provided by the vessel's operator. The extent to which the details are provided to perform a proper human reliability analysis, however, is insufficient in this report. The information is therefore used to perform a coarse SPAR-H, and some assumptions have to be made particularly on hypothetical Scenario 2. Assumptions that were made include there being sufficient time available for the DPO in Scenario 2, and the procedures being supportive for the OIM in Scenario 1, but less helpful to the DPO in Scenario 2. Moreover, the response from the DPO in Scenario 2 is also assumed, based on procedures. The assumptions are also presented in Table 5. The analysis was also affected by the hindsight bias, as are all incident investigations.

The authors believe that despite the limitations in verifying the data quality from incident reports, the information utilized in this study provides a useful starting point for risk model development, which can be updated at a later stage when necessary. In addition, it is typically not possible to successfully collect data for every incident in a DP system, but not all incidents need to be reported to be able to draw conclusions and identify key priorities to improve DP safety [33], or make better decisions.

5.4. Model uncertainties

Non-observable data, such as behavioral or mental states (e.g., operator belief and desire) that influence human error, also exist. These types of data influence the risk level of the system. In this study, BN is employed to infer latent variables. The child nodes of BN that take input parameters such as stress level or fitness for duty of the operator could consider data uncertainty. In this study, it is assumed that all input data have a 10% uncertainty.

It should be noted that the modeling results should be used in the decision-making process of the operator, and the level of uncertainty does not affect the comparison results between the two scenarios because it similarly influences them. Simply out, the results can be uncertain, but the ratio of uncertainty for all scenarios remain the same when we compare manual and automatic modes. The level of uncertainty, therefore, does not change the category of the scenario's risk level.

5.5. Online and dynamic risk management models

The proposed model can be used online because its input parameters can be updated continuously. The input parameters include the ESD initiator, operator characteristics accepted BNs, and failure frequency of components. The model can be used as an online tool to facilitate the decision-making process because its response time is less than 10 s.

The model, however, is not dynamic. Dynamic risk methodologies are generally those that utilize a time-dependent phenomenological model of system evolution and consider stochastic behavior to estimate the risk associated with the system response to an initiating event. These methodologies also employ a predictive model that generates branches at each user-specified time step or condition with their associated probabilities and computes the probability of each scenario. This feature provides a prediction of system behavior for each scenario that should be added to the model in future works.

5.6. Model Improvements and future work

5.6.1. Model improvement: decision support tool

The information from the risk management model can provide input to the decision support tool. The aim of the decision support tool is to provide the DPO with an overview of the risks associated with relevant decision alternatives. As mentioned earlier, the main judgement that a DPO has to make is whether or not she/he can safely remain on location or needs to move off location. The risk management model proposed in this paper can provide input into this decision process by presenting the failure probability and uncertainties of the current operation, including the risk of potential future failures and different decision alternatives.

5.6.2. Model improvement: decision alternatives

At present, the model does not include information regarding the consequences of decision alternatives. In the case of DP drilling units, one of the main barriers and consequences of the loss of position is well disconnection. The primary problem in drilling operations is the maintenance of hydrocarbon containment. In order to prevent the loss of containment, the DPO can decide to use the functionality of manually disconnecting the unit. If the available time is not sufficient, then the automated emergency disconnection should be activated when the MODU exceeds the red limit in its loss of position. The risks associated with these two scenarios (manual vs. automated disconnection) and the potential success of the disconnection in maintaining hydrocarbon containment can considerably differ. A manual disconnection situation can allow the DPO to communicate with the driller on the imminent disconnection so that the driller can secure the equipment in a manner that would optimize the success of disconnection (e.g., the drill bit does not block the shearing rams in the BOP). Additionally, the strain on the riser will be higher during the automated emergency disconnect versus the manual disconnect, increasing the risk of tearing the riser. This risk remains even though the riser angle limit at which the automated disconnect is set to be activated should protect the riser from tearing.

5.6.3. Model improvement: environmental factors

Environmental factors impact the risk associated with decision alternatives, which will be included in future work. The future conditions of weather, waves, and currents have a significant effect on the MODU's ability to maintain position and should be considered in the risk associated with decision alternatives.

5.6.4. Model improvement: weighting of decision outcome parameters

The risk management model in this study focuses on major risk hazards. There are also other risk, that should be considered. These can include time, material damage, and loss of reputation, which may influence the identification of the most optimal decision alternative. The authors are aware that the DP is simply a means for enabling complex operations. As such, it is not the "objective." The DP is necessary to enable drilling in certain areas. Drilling windows and schedules are disrupted by the choice to shift locations, and such decisions should be seriously contemplated. The primary focus of risk models is safety because an accident can be even more costly.

In future works, cost and time will be considered as decision outcome parameters. The weighting of these parameters, as well as the major hazard risk parameter, is a sensitive subject.

6. Conclusion

This paper proposes a risk management framework for a dynamic positioning system to assist operators in decision-making. The output of the risk management framework provides operators with a real-time risk status that can aid in making better decisions within a limited time. The framework presented in this paper also takes a more holistic approach to the risk modeling of DP operations by including human error scenarios both as initiating events and potentially escalating events.

The paper proposes a general risk management model for DP class 2 that can be used in a decision support tool. The developed model is based on 15 years of historical incident data of DP-related accidents and incidents. Moreover, human and organizational factors are considered in the risk management model using the Bayesian network model and the network is trained based on the SPAR-H method.

The proposed modelling approach is generic, and in this paper, it is applied to a DP drilling unit as a case study. The frequencies and probabilities of initial events of the DP drilling unit are first determined by cleaning the gathered data from the IMCA reports. Human errors are thereafter quantified using the SPAR-H method and based on relevant PSFs. In order to evaluate the framework effectiveness, two scenarios in automatic and manual modes are thereafter compared.

The results show that the SPAR-H and Bayesian network approaches are potential methods for considering the human and organizational factors in risk management. Moreover, the comparison results between the manual and automatic modes show that the proposed risk management model can be an appropriate tool for risk-informed decision-making. In this study, the decision-making process is based on system failure probability. Other parameters, such as cost and time limitation, could be implemented in the developed framework.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

CRediT authorship contribution statement

Tarannom Parhizkar: Data curation, Writing - original draft. **Sandra Hogenboom:** Data curation, Investigation, Writing - review & editing. **Jan Erik Vinnem:** Conceptualization, Methodology, Writing - review & editing, Supervision. **Ingrid Bouwer Utne:** Conceptualization, Methodology, Writing - review & editing, Supervision.

References

[1] Volkanovski A, Cepin M. Implication of PSA uncertainties on risk-informed decision making. Nucl Eng Des 2011;241(4):1108–13.
[2] Mehr AF, Irem TY. Risk-based decision-making for managing resources during the design of complex space. J Mech De. 2006;128(4):1014–22.
[3] The International Marine Contractors Association. Dynamic positioning station keeping review. Incidents and events reported for 2016. International Marine Contractors Assosiation, 2018.
[4] Parhizkar T, Aramoun F, Esbati S, Saboohi SY. Efficient performance monitoring of building central heating system using Bayesian Network method. J Build Eng 2019;26:100835.
[5] Utne IB, Schjølberg I, Roe E. High reliability management and control operator risks in autonomous marine systems and operations. Ocean Eng 2019;171:399–416.
[6] Parhizkar T, Balali S, Mosleh A. An entropy based bayesian network framework for system health monitoring. Entropy 2018;20(6):416.
[7] Vinnem JE, Utne IB, Schjølberg I. On the need for online decision support in FPSO–shuttle tanker collision risk reduction. Ocean Eng 2015;101:109–17.
[8] NASA N. Risk-informed decision making handbook. Washington, DC: NASA Headquarters; 2010.
[9] Liu Y, Frangopol DM, Cheng M. Risk-informed structural repair decision making for service life extension of aging naval ships. Mar Struct 2019;64:305–21.
[10] Shah LA, Etienne A, Siadat A, Vernadat FB. Performance visualization in industrial performance visualization in industrial. IFAC-PapersOnLine 2018;51(11):552–7.
[11] Kongsvik T, Almklov P, Haavik T, Haugen S, Vinnem JE, Schiefloe PM. Journal of loss prevention in the process industries decisions and decision support for major accident prevention in the process industries. J Loss Prev Process Ind 2015;35:85–94.
[12] Yang X, Haugen S. Risk information for operational decision-making in the offshore oil and gas industry. Saf Sci 2016;86:98–109.
[13] B. Rokseth, I.B. Utne, and J.E. Vinnem, "A systems approach to risk analysis of maritime operations," vol. 231, no. 1, pp. 53–68, 2017.
[14] Bø TI, Johansen TA, Sorensen AJ, Mathiesen E. Dynamic consequence analysis of marine electric power plant in dynamic positioning. Appl Ocean Res 2016;57:30–9.
[15] V. Khorasani, "Risk assessment of diesel engine failure in a dynamic positioning system," Master Thesis, Faculty of Science and Technology, University of Stavanger, 2015.
[16] Vedachalam N, Ramadass GA. Reliability assessment of multi-megawatt capacity offshore dynamic positioning systems. Phys Procedia 2017;63:251–61.
[17] Hogenboom S, Rokseth B, Vinnem JE, Utne IB. Human reliability and the impact of control function allocation in the design of dynamic positioning systems. Reliab Eng Syst Saf 2020;194:106340.
[18] Parhizkar T, Aramoun F, Saboohi Y. Efficient health monitoring of buildings using failure modes and effects analysis case study: air handling unit system. J Build Eng 2020;29:101113.
[19] N. NASA, "Probabilistic Risk Assessment Procedures Guide for Offshore Applications (DRAFT) report", 2017. https://www.bsee.gov/sites/bsee.gov/files/ProbalisticRiskAssessment%20%28PRA%29/bsee_pra_procedures_guide_-_10-26-17.pdf.
[20] "www.dynamicpositioning.guru.com," 2015. [Online].
[21] I. Pil, "Causes of dynamic positioning system failures and their effect on dp vessel," Master Thesis, Estonian Maritime Academy, Tallinn University of Technology, 2018.
[22] Wells G. Hazard identification and risk assessment. IChemE; 1996.
[23] The International Marine Contractors Association, "Dynamic positioning station keeping review, incidents and events reported for (2004–2015)," International Marine Contractors Assosiation, 2005–2017.
[24] Stamatis DH. Failure mode and effect analysis: FMEA from theory to execution. ASQ Quality press; 2003.
[25] Reason J. Managing the risks of organizational accidents. Routledge; 2016.
[26] Rasmussen J. Human errors. A taxonomy for describing human malfunction in industrial installations. J Occup Accid 1982;4(2–4):311–33.
[27] Reason J. Human error. New York: Cambridge University Press; 1990.
[28] Groth K, Wang C, Mosleh A. Hybrid causal methodology and software platform for probabilistic risk assessment and safety monitoring of socio-technical systems. Reliab Eng Syst Saf 2010;95(12):1276–85.
[29] Hakonsund K. Investigation report level 2, Rig excrusion reached red watch circle. Odfjell Drilling, Synergi 2018;209204:1–19.
[30] Chen H, Nygärd B. Quantified risk analysis of DP operations-principles and challenges. SPE International Conference and Exhibition on Health, Safety, Security, Environment, and Social Responsibility. Society of Petroleum Engineers; 2016.
[31] Groth KM, Swiler LP. Use of a SPAR-H Bayesian network for predicting human error probabilities with missing observations. 11th international probabilistic safety assessment and management conference. 2012.
[32] R. Woodward, "The organisation for economic co-operation and development (OECD)," Routledge, 2009.
[33] S. Thompson, "Safety Data Management and Governance, Developing and Implementing Safety Data Business Plans report," US department of Transportation, Federal highway administration, 2016. https://safety.fhwa.dot.gov/rsdp/manage.aspx.